

# Global Optimization: For Some Problems, There's HOPE

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# Outline

- Problem and Existing Methods
- Homotopy Optimization Methods
- Protein Structure Prediction Problem
- Numerical Experiments
- Conclusions/Future Directions

# Problem

- Solve the **unconstrained minimization** problem

$$f(x^*) = \min_{x \in \mathbb{R}^n} f(x) \quad (f : \mathbb{R}^n \rightarrow \mathbb{R})$$

- **Function Characteristics**

- Solution exists, smooth ( $f \in C^2(\mathbb{R}^n, \mathbb{R})$ )
- Complicated (multiple minima, deep local minima)
- Good starting points unknown/difficult to compute

- **Challenges**

- Finding solution in reasonable amount of time
- Knowing when solution has been found

# Some Existing Methods

- Exhaustive/enumerative search
  - Stochastic search [Spall, 2003]; adaptive [Zabinsky, 2003]
  - “Globalized” local search [Pinter, 1996]
  - Branch and bound [Horst and Tuy, 1996]
  - Genetic/evolutionary [Voss, 1999]
- Smoothing methods [Piela, 2002]
  - Simulated annealing [Salamon, et al., 2002]
  - Homotopy/continuation methods [Watson, 2000]

# Outline

- Problem and Existing Methods
- **Homotopy Optimization Methods**
- Protein Structure Prediction Problem
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# Homotopy Methods for Solving Nonlinear Equations

- Goal

- Solve complicated nonlinear **target** system

$$f_1(x) = 0, \quad (f_1 : \mathbb{R}^n \rightarrow \mathbb{R}^n)$$

- Steps to solution

- Easy **template** system:  $f_0(x^0) = 0$  ( $x^0$  *known*)

- Define a continuous **homotopy** function:

- $$h(x, \lambda) = \begin{cases} f_0(x), & \text{if } \lambda = 0 \\ f_1(x), & \text{if } \lambda = 1 \end{cases}$$

- Example (convex):  $h(x, \lambda) = (1 - \lambda)f_0(x) + \lambda f_1(x)$

- Trace path of  $h(x, \lambda) = 0$  from  $\lambda = 0$  to  $\lambda = 1$

# Homotopy Optimization Methods (HOM)

- Goal

- Minimize complicated nonlinear **target** function

$$\min_{x \in \mathbb{R}^n} f_1(x), \quad (f_1 : \mathbb{R}^n \rightarrow \mathbb{R})$$

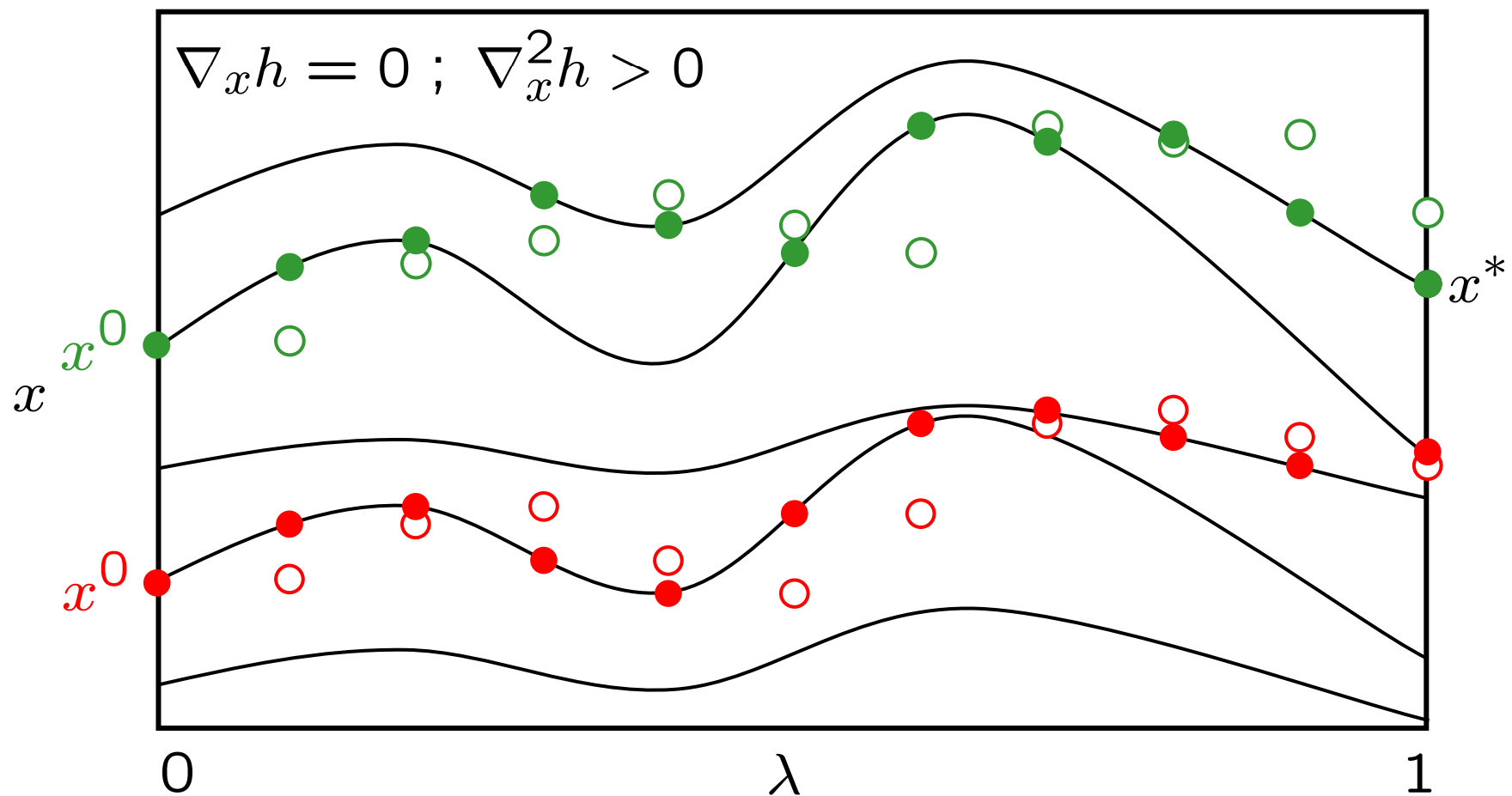
- Steps to solution

- Easy **template** function:  $f_0(x^0) = \min_{x \in \mathbb{R}^n} f_0(x)$
- Define a continuous **homotopy** function:
  - $h(x, \lambda) = \begin{cases} f_0(x), & \text{if } \lambda = 0 \\ f_1(x), & \text{if } \lambda = 1 \end{cases}$
  - Example (convex):  $h(x, \lambda) = (1 - \lambda)f_0(x) + \lambda f_1(x)$
- Produce sequence of minimizers of  $h(x, \lambda)$  w.r.t.  $x$  starting at  $\lambda = 0$  and ending at  $\lambda = 1$

# Illustration of HOM

$$x^* = \min_{x \in \mathbb{R}} f_1(x)$$

$$h(x, \lambda) = (1-\lambda)f_0(x) + \lambda f_1(x)$$





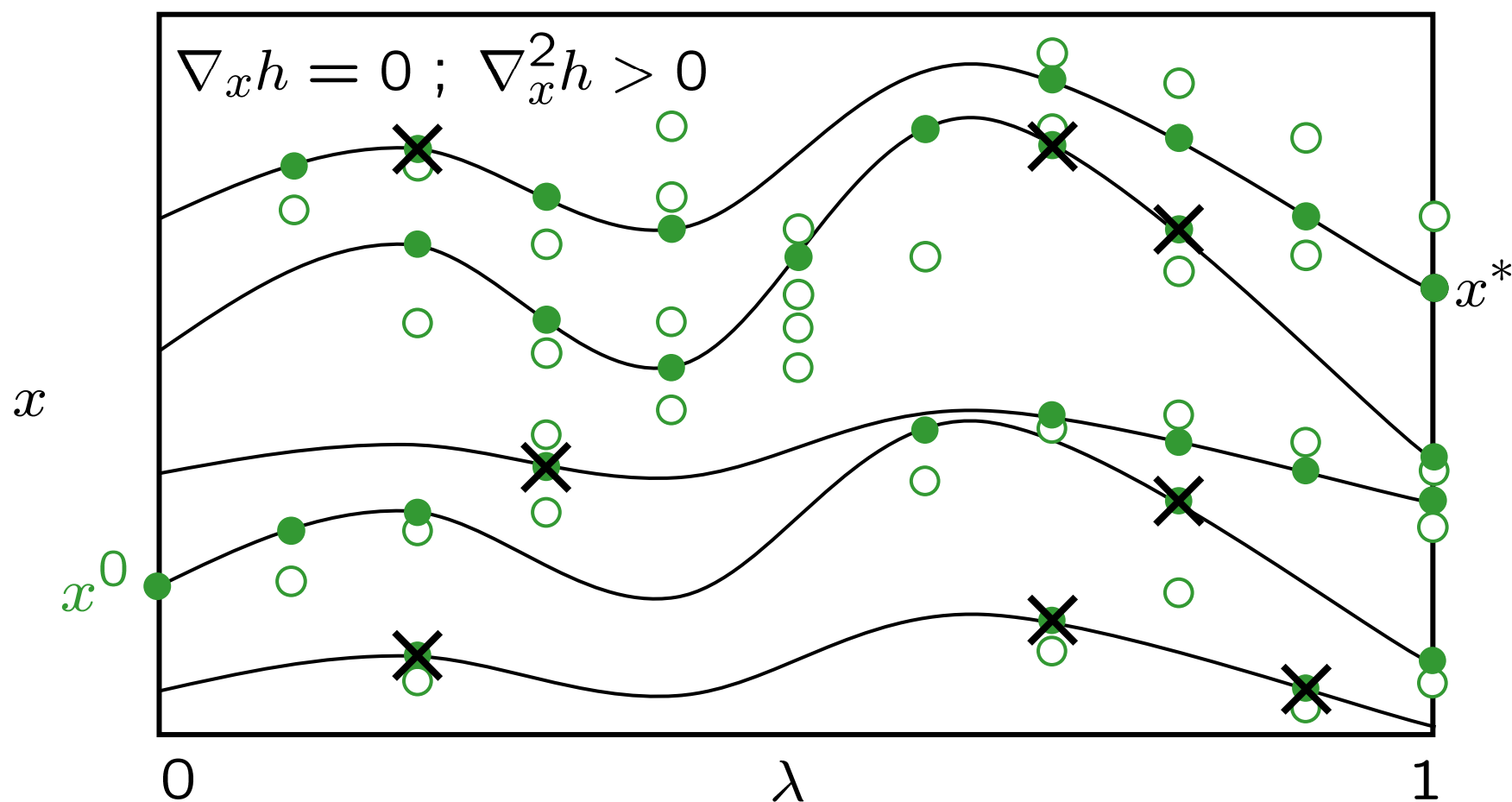
# Homotopy Optimization using Perturbations & Ensembles (HOPE)

- Improvements over HOM
  - Produces ensemble of sequences of **local** minimizers of  $h(x, \lambda)$  by perturbing intermediate results
  - Increases likelihood of predicting **global** minimizer
- Algorithmic considerations
  - Maximum ensemble size
  - Determining ensemble members

# Illustration of HOPE

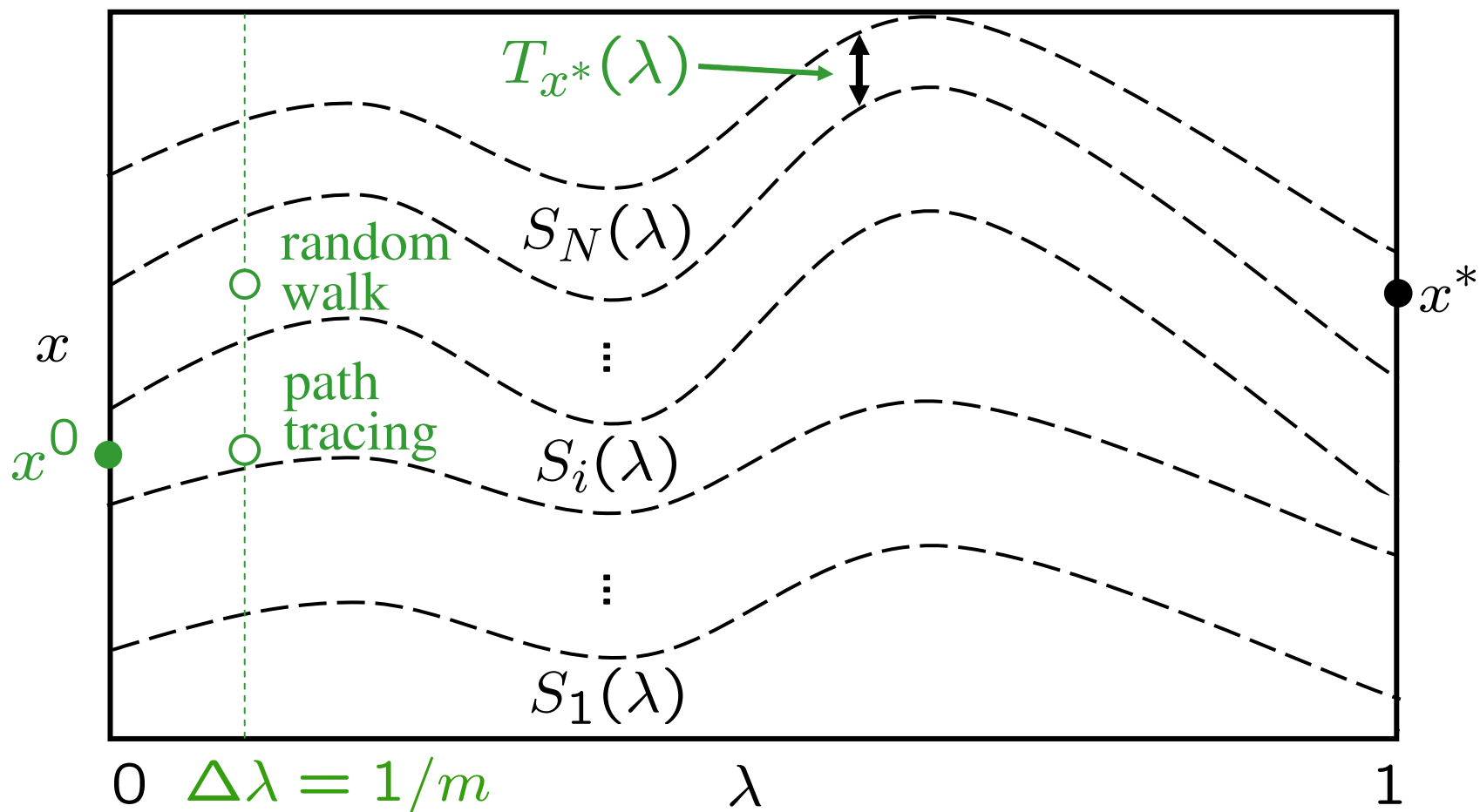
**Constraint:** ensemble size  $\equiv |\mathbb{E}| \leq 2$

$$x^* = \min_{x \in \mathbb{R}} f_1(x) \quad h(x, \lambda) = (1-\lambda)f_0(x) + \lambda f_1(x)$$



# Convergence of HOPE

**Goal:**  $m \in \mathbb{Z}^+$  s.t.  $\mathcal{P}(\exists x \in \mathbb{E}_m | x \in S_N) > \rho$



# Convergence of HOPE

$$\alpha = \min_{\lambda \in [0,1]} \{T_{x^*}(\lambda)\} \quad P = \begin{bmatrix} 1-2\alpha & \alpha & & & & \alpha \\ \alpha & 1-2\alpha & \alpha & & & \\ & \ddots & \ddots & \ddots & & \\ & & \alpha & 1-2\alpha & \alpha & \\ \alpha & & & \alpha & 1-2\alpha \end{bmatrix}$$


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No constraints on ensemble size:  $|\mathbb{E}_m| = 2^m$

$$\mathbb{E}_0 = \{x^0\} ; \mathbb{E}_k = \mathbb{E}_{k-1} \cup \{\text{perturbed versions of } \mathbb{E}_{k-1}\}$$


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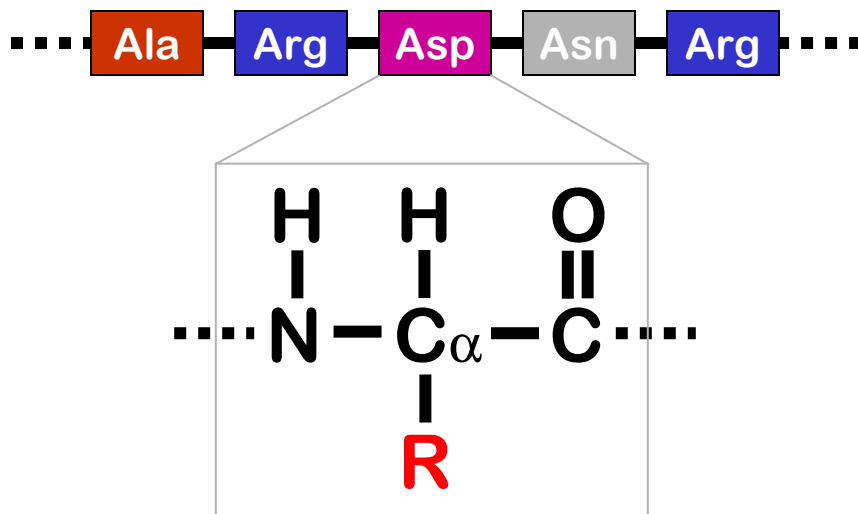
$$\begin{aligned} \mathcal{P}(\exists x \in \mathbb{E}_m : x \in S_N) &= 1 - \prod_{k=0}^m \left(1 - e_i^T P^k e_N\right)^{\binom{m}{k}} \\ &\geq 1 - \prod_{k=\kappa}^m \left(1 - P_{N/2,N}^k\right)^{\binom{m}{k}} \quad (\kappa = \min\{i, N-i\}) \\ &= 1 - \prod_{k=\kappa}^m \left(1 - \frac{1}{N} \sum_{l=0}^{N-1} (-1)^l \left(1 - 2\alpha + 2\alpha \cos\left(\frac{2\pi l}{N}\right)\right)^k\right) \end{aligned}$$

# Outline

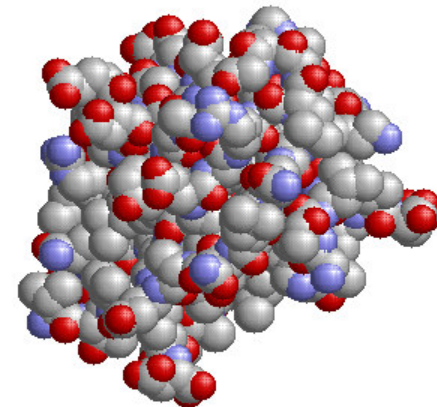
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# Protein Structure Prediction

Amino Acid Sequence



Protein Structure



Given the amino acid sequence of a protein (1D), is it possible to predict its native structure (3D)?

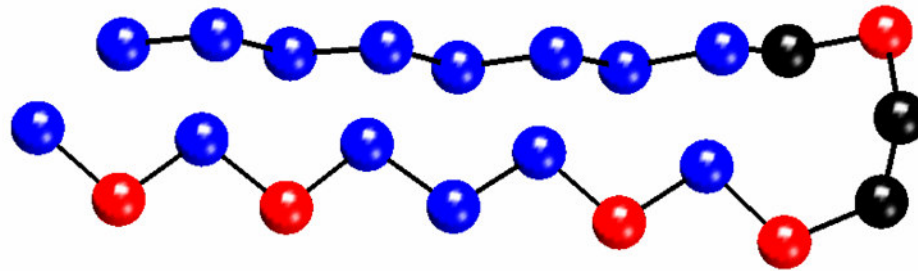
# Protein Structure Prediction

- Given:
  - Protein model
    - Molecular properties
    - Potential energy function (force field)
- Goal:
  - Predict lowest energy conformation
    - Native structure [Anfinsen, 1973]
  - Develop hybrid method, combining:
    - Energy minimization [numerical optimization]
    - Comparative modeling [bioinformatics]
      - Use **template** (known structure) to predict **target** structure

# Protein Model: Particle Properties

- Backbone model

- Single chain of particles with residue attributes
- Particles model  $C_{\alpha}$  atoms in proteins



- Properties of particles

- Hydrophobic, Hydrophilic, Neutral
- Diverse hydrophobic-hydrophobic interactions

[Veitshans, Klimov, and Thirumalai. *Protein Folding Kinetics*, 1996.]

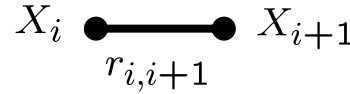


# Protein Model: Energy Function

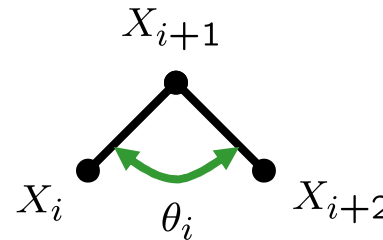
$$E(X) = E_{bl}(X) + E_{ba}(X) + E_{dih}(X) + E_{non}(X)$$


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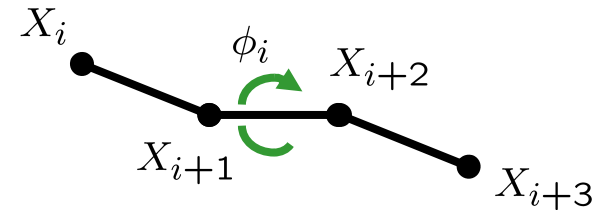
$$E_{bl}(X) = \sum_{i=1}^{n-1} \frac{k_r}{2} (r_{i,i+1} - \bar{r})^2$$



$$E_{ba}(X) = \sum_{i=1}^{n-2} \frac{k_\theta}{2} (\theta_i - \bar{\theta})^2$$



$$E_{dih}(X) = \sum_{i=1}^{n-3} [A_i(1 + \cos \phi_i) + B_i(1 + \cos 3\phi_i)]$$



$$E_{non}(X) = \sum_{i=1}^{n-3} \sum_{j=i+3}^n \gamma_{ij} \left\{ \alpha_{ij} \left( \frac{\bar{r}}{r_{ij}} \right)^{12} - \beta_{ij} \left( \frac{\bar{r}}{r_{ij}} \right)^6 \right\}$$

# Homotopy Optimization Method for Proteins

- Goal

- Minimize energy function of **target** protein

$$\min_{X \in \mathbb{R}^{3n}} E^1(X), \quad (E^1 : \mathbb{R}^{3n} \rightarrow \mathbb{R})$$

- Steps to solution

- Energy of **template** protein:  $E^0(X^0) = \min_{X \in \mathbb{R}^{3n}} E^0(X)$
- Define a **homotopy** function:
  - $H(X, \lambda) = \rho^0(\lambda)E^0(X) + \rho^1(\lambda)E^1(X)$
  - Deforms template protein into target protein
- Produce sequence of minimizers of  $H(X, \lambda)$  starting at  $\lambda = 0$  and ending at  $\lambda = 1$

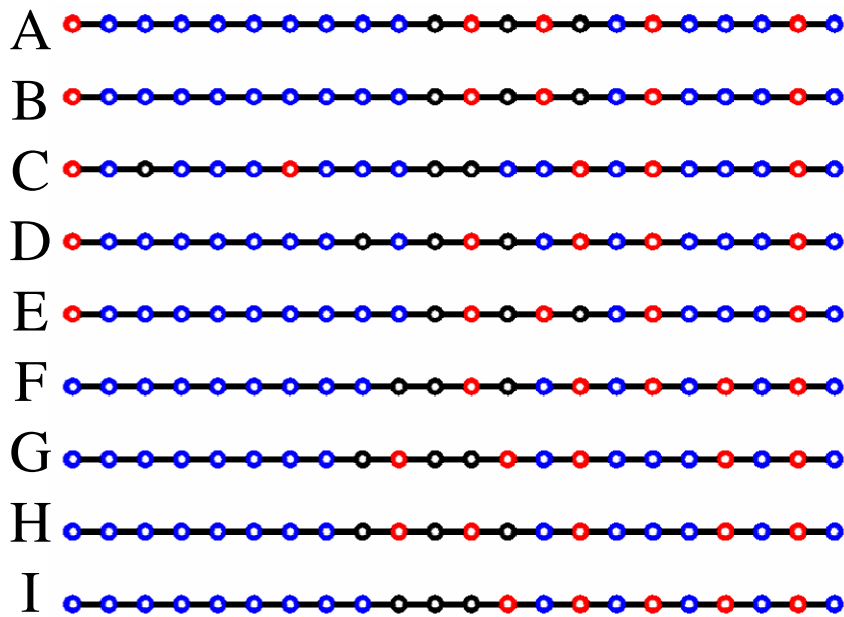
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# Numerical Experiments

9 chains (22 particles) with known structure

Loop Region

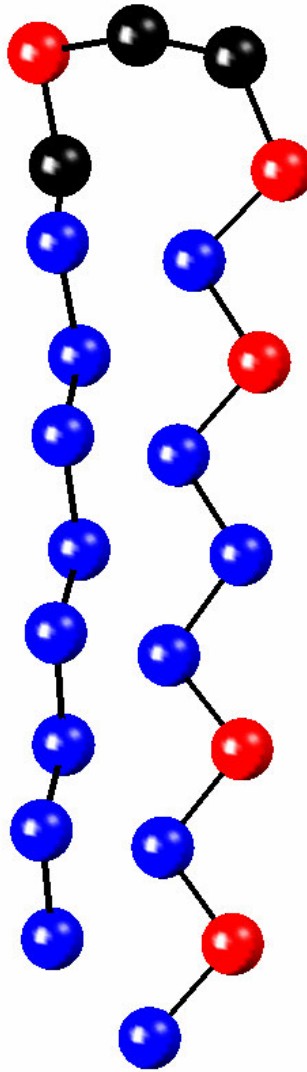


Hydrophobic    Hydrophilic    Neutral

Sequence Matching (%)

	A	B	C	D	E	F	G	H	I
A	100								
B	77	100							
C	86	91	100						
D	91	86	77	100					
E	73	82	73	82	100				
F	68	68	59	77	86	100			
G	68	68	59	77	86	100	100		
H	68	68	59	77	86	100	100	100	
I	73	59	64	68	77	73	73	73	100

# Numerical Experiments



# Numerical Experiments

- 62 template-target pairs
  - 10 pairs had identical native structures
- Methods
  - HOM vs. Newton's method w/trust region (N-TR)
  - HOPE vs. simulated annealing (SA)
    - Different ensemble sizes (2,4,8,16)
    - Averaged over 10 runs
    - Perturbations where sequences differ
- Measuring success
  - Structural overlap function:  $0 \leq \chi \leq 1$ 
    - Percentage of interparticle distances off by more than 20% of the average bond length ( $\bar{r}$ )
  - Root mean-squared deviation (RMSD)

Ensemble SA  
Basin hopping  
 $T_0 = 10^5$   
Cycles = 10  
Berkeley schedule

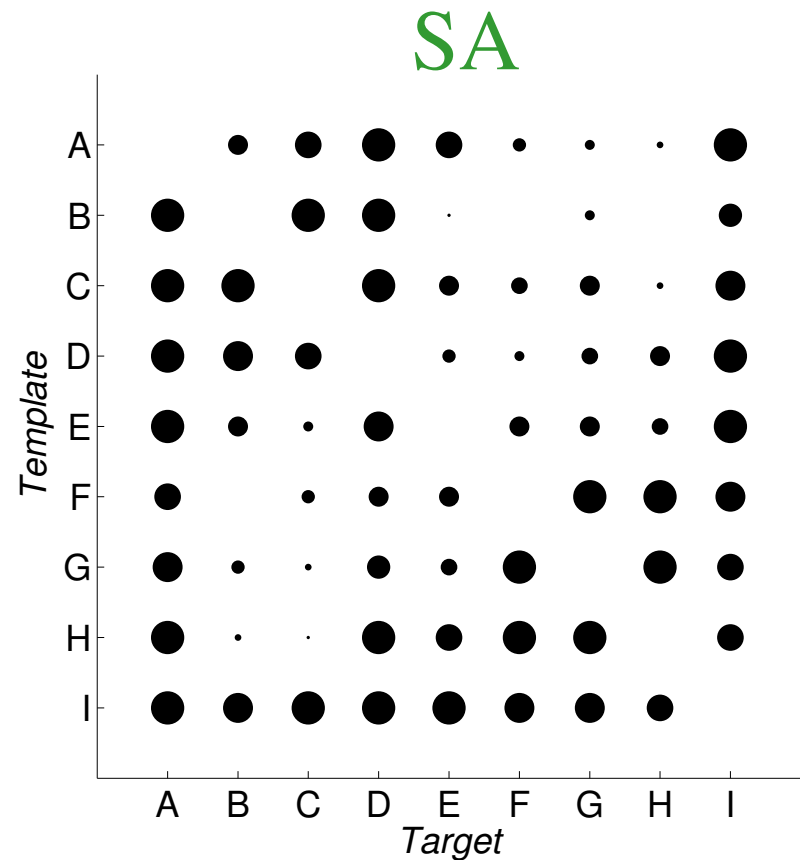
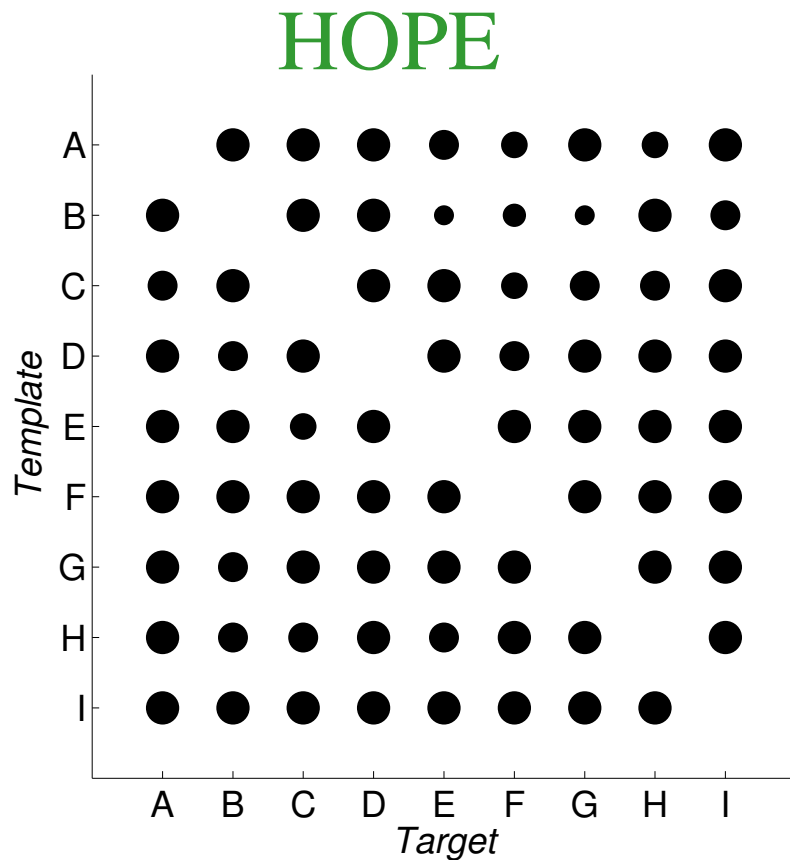
# Results

Method		$\chi = 0$	Success	Mean $\chi$	Mean RMSD	Time (sec)
<i>HOM</i>		<b>15</b>	<b>0.24</b>	<b>0.36</b>	<b>0.38</b>	<b>10</b>
<i>N-TR</i>		4	0.06	0.45	0.55	1

Method	Ensemble Size	$\chi = 0$	Success	Mean $\chi$	Mean RMSD	Time (sec)
<i>HOPE</i>	2	33.40	0.54	0.14	0.17	35
	4	43.10	0.70	0.08	0.11	65
	8	54.60	0.88	0.03	0.04	115
	<b>16</b>	<b>59.00</b>	<b>0.95</b>	<b>0.01</b>	<b>0.02</b>	<b>200</b>
<i>SA</i>	2	13.10	0.21	0.27	0.36	52
	4	20.80	0.34	0.19	0.26	107
	8	28.50	0.46	0.13	0.19	229
	16	40.20	0.65	0.08	0.12	434

# Results

Success of HOPE and SA with ensembles of size 16 for each template-target pair. The size of each circle represents the percentage of successful predictions over the 10 runs.





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# Conclusions

- Homotopy optimization methods
  - More successful than standard minimizers
- HOPE
  - For problems with  $f^0, x^0$  ( $E^0, X^0$ ) readily available
  - Solves protein structure prediction problem
  - Outperforms ensemble-based simulated annealing
    - No fine tuning of SA

# HOPEful Directions

- Protein structure prediction
  - Protein Data Bank (templates), TINKER (energy)
  - Probabilistic convergence analysis ( $\mathbb{R}^n$ )
- HOPE for large-scale problems
  - Inherently parallelizable
  - Communication: enforce maximum ensemble size
- Sandia
  - Protein structure prediction (Bundler)
  - LOCA, APPSPACK
  - SGOPT

# Other Work/Interests

- Optimization
  - Surrogate models in APPSPACK (Sandia)
- Linear Algebra
  - Structure preserving eigensolvers
    - Quaternion-based Jacobi-like methods
  - RF circuit design – efficient DAE solvers
    - Preconditioners, harmonic-balance methods
- Information processing/extraction
  - Entity recognition/disambiguation
    - Persons, locations, organization
  - Querying, clustering and summarizing documents

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- Dianne O'Leary (UM)
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**Daniel Dunlavy – HOPE**

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